Network-Level Adaptive Signal Control Optimization Under a Closed-Loop Online Updating Framework

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SHORT SUMMARY

Adaptive signal control is a flexible solution for network signal control but the tradeoff between computational complexity and solution quality is long-standing, especially for large-scale network. Besides, prediction accuracy of the future traffic state also carries considerable weight in control efficacy. Therefore, this study proposed a centralized cycle-based adaptive traffic light control (CATLC) model to optimize the green time of each intersection on a cyclic basis aiming at network delay minimization under a network signal control framework using a closed online updating strategy. Using the real-time link volume measurement, the cycle-based link turning ratio is predicted through a gated recurrent unit (GRU) deep learning network trained with incremental historical data to update the parameters of the CATLC model. An extended multi-cycle-based adaptive traffic light control (MCATLC) method is further developed based on model predictive control (MPC) strategy, which extends the prediction step to multiple cycles considering traffic progression in the neighborhood of each intersection. Simulation evaluation was conducted through SUMO with a network of 56 intersections in Singapore, and the MCATLC showed an improvement of over 44% and 19% in waiting time, compared with the fixed time scheme and SCATS scheme, respectively, which is promising for real-time control in practice.

Keywords: Cycle-based adaptive network signal control, closed-loop online updating strategy, delay minimization, turning ratio prediction, model predictive control

1. INTRODUCTION

With increasing population and number of vehicles, traffic congestion becomes one of the major bottlenecks of the societal development. Efficient traffic signal control is a viable alternative solution as compared with continuously expanding the road space, which is realized by providing adequate right-of-way for traffic demands of different origin-destination pairs and different paths. Considering the increasingly complicated traffic demand pattern and availability of real-time traffic flow data, adaptive signal control can cope with fluctuations in the traffic flow more efficiently than fixed-time control and actuated control, with accurate foresight to learn about the demand changes caused by internal and external factors (Wang et al., 2018).

Regarding centralized adaptive signal control for large-scale network which remains NP-complete even with strong assumptions on traffic dynamics (Zhang et al., 2022), the balance between prediction accuracy of the overall traffic environment for a better control performance and the corresponding complexity or computation cost is always a hot spot. Two main directions in literature, suboptimal approaches based on simplifications in traffic modeling and suboptimal approaches based on heuristics optimization are developed. Simplification in traffic modeling aims to formulate the network control problem as a simple or tractable paradigm to fit in with mature solution algorithms, such as CTM model (Daganzo, 1994; Lo, 2001), TUC model (Aboudolas et al., 2010), etc. Such efforts in modeling simplification reaped a good scalability thanks to analyzable formulations, but some parameters concerning network topology of network, route choice and demand distribution are mostly predefined and fixed, weakening the network control performance and method applicability. Regarding the suboptimal approaches based on heuristics optimization, metaheuristic algorithms are considered as a new trend in recent years due to their simple coding strategy and better performance with considerable cost savings. On the way of improving the applicability of different existing metaheuristic algorithms in practical network signal control scenarios (Leal et al., 2017), a general consensus about the difficulties lies in the computational complexity with the increase in network scale as well as the balance between generalization of heuristic strategies and case-based parameter setting (Noaeen et al., 2021).

Therefore, in this paper, a centralized cycle-based adaptive traffic light control (CATLC) model is formulated for large-scale roadway network using a closed-loop online updating strategy. Based on a model predictive control (MPC) strategy, an extended multi-cycle adaptive traffic light control (MCATLC) model is further proposed considering a longer prediction horizon of the traffic state. Under the closed-loop control framework, the turning ratio of each link will be predicted using a gated recurrent unit (GRU) deep learning network trained with historical data, thus the demand pattern of the network can be learned and input to the CATLC model. Aimed at minimization of total network delay for each cycle, the green times of each phase are optimized using an improved differential evolutionary (IDE) algorithm. With the proposed signal controller, parameter predictor and the optimization solver, the network signal control is realized in a self-learning and self-adaptive way.

2. METHODOLOGY

Aimed at the research scenario of a large-scale urban signalized roadway network, the proposed signal control optimization is expected to be realized under a closed software-in-the-loop simulation-based control framework as shown in Figure 1. The core of the proposed control framework is a centralized signal controller using CATLC model and its extension MCATLC model, whose input is real-time link flow data obtained through detectors, as well as the turning ratio reflecting network demand distribution obtained by a deep learning-based predictor. The (M)CATLC model is solved through an improved differential evolutionary (IDE) algorithm solver. An online updating strategy is adopted here to continuously update the parameters including turning ratio, link velocity, link density, etc., so that network signal control optimization can be realized through self-learning of traffic demand pattern and self-adaption of right-of-way assignment.

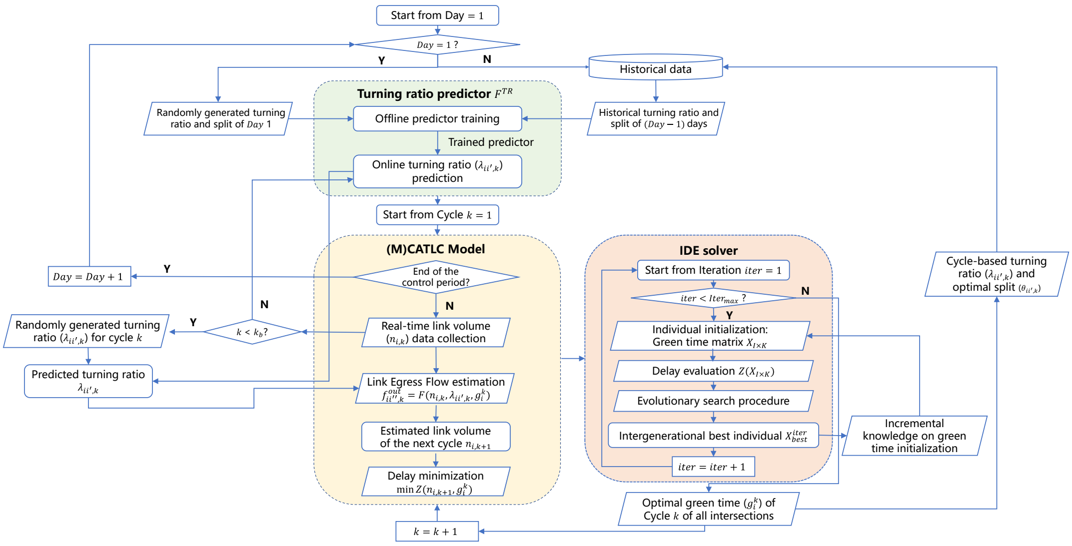

Figure 1 Closed-loop online control framework

2.1. CATLC Signal Controller

In the CATLC model, a flow dynamic model is used to formulate the conservation law for the link volume dynamics based on the CTM model and LWR principle. The link egress flow is formulated as a nonlinear mixed logical switching function considering heterogeneous kinematics of dissipating flows of different directions at the intersection. On a cyclic basis, the maximal egress flow is constrained by the saturation flow which is determined by the calibrated link density and link speed, while the traffic demand arriving at a specific link can be estimated by the cycle-based turning ratio. Under such constraints, the objective of the signal controller is to minimize the cycle-based network delay, which is formulated as the weighted sum of the average travel delay of each link. Motivated by the possibility of solution quality improvement with a broader vision of how the traffic demand will aggregate and dissipate in the neighborhood of a certain intersection, the extended MCATLC model is proposed to optimize the splits of the next several cycles aiming to minimize the corresponding estimated network delay using the same input as CATLC model. Based on a MPC strategy, the optimization of MCATLC is realized in a receding horizon control pattern with a reliable accuracy of the link flow dynamics model.

2.2 Learning-based Turning Ratio Predictor

Considering the continuity and stability of daily traffic demand as well as its temporal-spatial distribution, a turning ratio prediction method is proposed using a gated recurrent unit (GRU) deep learning algorithm, regarding the turning ratio as a function in terms of turning ratio and split in the previous multiple cycles. Considering real-time control within a period in practice, the historical data of the same period over the past days can be used for predictor training in an offline way, then the trained predictor will be used for online prediction with turning ratio and signal data during the past cycles on the same day as input. In this way, the GRU deep learning-based predictor is updated through incremental training to learn the temporal-spatial demand pattern in a daily self-tuning way.

2.3 Improved Differential Evolutionary Solver

The CATLC model is a large-scale non-convex optimization problem. Based on the NP-hard real-time discrete property of this non-linear integer programming model and the specific signal control scenario, an improved differential evolution (IDE) algorithm is proposed. An initialization step featuring incremental knowledge is used to initialize the individuals (namely the green time) based on a feasible zone constructed by incremental historical solution record data, instead of the random initialization used in general DE algorithm. In other words, the upper and lower boundaries of green time of each phase will be updated with incremental historical data, which makes the optimum searching more efficient.

3. EVALUATION

The proposed method was evaluated using a closed-loop simulation testbed built based on the Jurong West area in Singapore, consisting of 56 signalized intersections (including 26 crossroads and 30 T-type junctions) as shown in Figure 2. Based on the historical detector data, the vehicle input of a total of 24 origin/destination areas and 1052 paths were calibrated. The simulation period is set as 7200s with a total traffic load of 18489 veh as input, which implies a medium-to-high level of traffic demand. The cycle length is set as 90s for all the intersections.

As shown in Figure 3, the evaluation procedure consists of three modules. The traffic simulator is built using the SUMO (Simulation of Urban Mobility) software and provides real-time link volume for predictor and controller through the 'TraCI' interface. Based on the cyclic link volume, the GRU predictor is trained using historical data offline and predicts the turning ratio of each cycle as one of the inputs of the signal controller. Using the real-time link volume and predicted turning ratio, the controller returns the optimized green time allocation of the next cycle to the simulator.

Figure 2 Simulation case study site

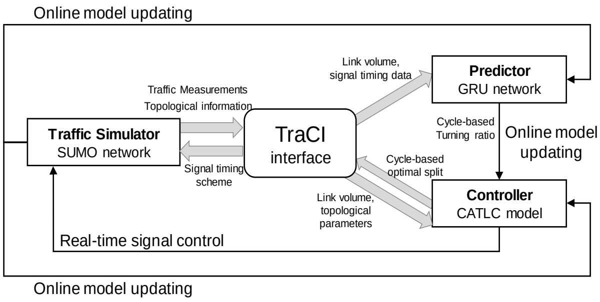

Figure 3 Simulation testbed components

For horizontal comparison, fixed timing scheme, gap-based and delay-based actuated scheme (Lopez et al., 2018), SCATS schemes (Liu and Chen, 2004) using common cycle length and cycle length optimization (hereinafter referred to as SCATS Scheme 1 and SCATS Scheme 2, respectively) are also designed and tested under the same scenario. The extended MCATLC model were tested using different control steps ranging from 2 cycles to 5 cycles. In order to evaluate the control performance of all such timing schemes, two indexes, total waiting time and average travel speed were selected, and each timing scheme was tested with ten parallel experiments to guarantee the generality of the results.

As show in Figure 4, the overall performance of the CATLC method is better than the fixed time scheme, the delay-based actuated scheme, the gap-based actuated scheme, SCATS Scheme 1 and SCATS Scheme 2 by 35.3%, 26.9%, 4.9%, 20.2% and 6.5% in terms of the total waiting time, respectively. With the increase of the control step, the control performance of MCATLC model gets gradually better until 5-cycle. The 2-cycle scheme is already ahead of all other schemes in all evaluation indexes. Although the improvement range gets smaller with the increase of the control step, the 4-cycle MCATLC model can be regarded to have the best control performance among all the signal timing schemes, with an improvement of 44.5%, 18.5% and 19.8% in total waiting time over the selected fixed-time scheme, actuated scheme (gap-based) and adaptive scheme (SCATS Scheme 2), respectively. Regarding the computation cost of the proposed method, the average optimization cost is 2.12s for CATLC model, showing a promising prospect in real-time control application.

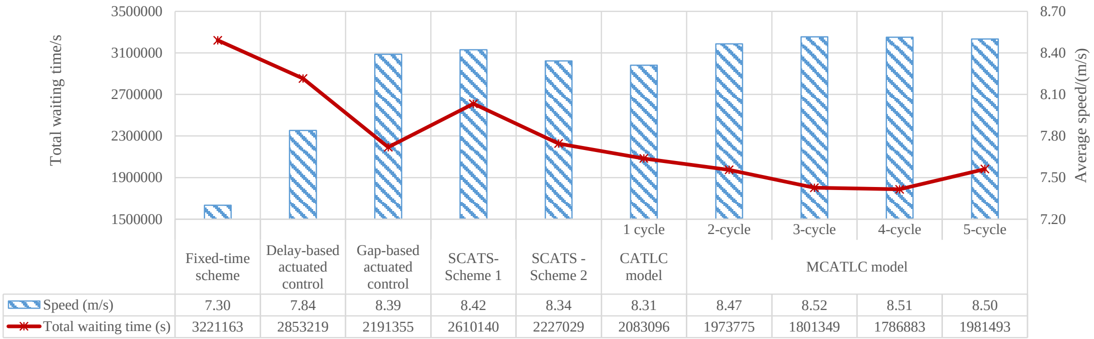

Figure 4 Control performance comparison of different signal timing schemes

4. CONCLUSIONS AND RESEARCH SIGNIFICANCE

To fill the research gap in current network adaptive signal control problem, a centralized multi-cycle-based adaptive traffic signal control model is proposed aiming at network delay minimization under a closed-loop online updating framework. Evaluation indicated that the proposed method is superior to the existing fixed time control, actuated control and adaptive control scheme by more than 18%.

On the theoretical side, heterogeneity of different turning flows and the correlation between consecutive intersections can be captured using online updating link dynamics model based on deep learning-based demand prediction, and the MPC-based receding control pattern. It guarantees the control efficacy and avoids the myopic decision-making of the existing adaptive signal control, especially for complicated and volatile demand scenarios.

On the practical side, the metaheuristic IDE solver enables the proposed method to meet the real-time requirements of large-scale network control with satisfactory solution quality. The incremental learning and fine-tuning mechanism also make the most of the available traffic detection data.

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